

REVIEW

Toward Smart City Skyways: 6G-Enabled Antenna Architectures and Adaptive Channel Modeling for Urban Low-Altitude UAV Network

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Abstract: Low-altitude unmanned aerial vehicle (UAV) communication in cities is affected by frequent blockage, rapidly changing propagation paths, limited onboard power, and strict latency requirements. These conditions make it difficult to evaluate channel models, antenna designs, and communication algorithms in a single layer. This review discusses how sixth-generation research approaches the problem through urban channel characterization, reconfigurable intelligent surfaces, metamaterial antennas, and data-driven communication control. It covers material-dependent propagation, dynamic blockage, channel prediction, beam management, trajectory planning, resource allocation, federated learning, and integrated sensing and communication. The literature is compared by operating frequency, urban scenario, validation basis, and trade-offs among reliability, delay, energy consumption, and hardware complexity. Results reported for any one method remain conditional and do not show that an end-to-end UAV link will operate reliably under representative urban conditions. Such performance also depends on representative channel measurements, update latency, hardware nonidealities, and the size, weight, power, and cost limits of the platform. The review identifies shared datasets, integrated field experiments, and reproducible benchmarks, including Digital Twin evaluations, as the next requirements for translating laboratory and simulation results into dependable, scalable Smart City Skyways.

Keywords: 6G, UAV communication, reconfigurable intelligent surfaces, channel characterization, AI-driven optimization

1. Introduction

Research on sixth-generation (6G) networks is motivated in part by applications whose connectivity, intelligence, or latency requirements cannot be adequately met by current fifth-generation (5G) systems [1–3]. Low-altitude unmanned aerial vehicles (UAVs) are one such application. Their potential uses in cities include parcel delivery, traffic monitoring, emergency response, infrastructure inspection, and urban air mobility [4]. Supporting these operations calls for broadband communication and low-latency command transmission, together with situational awareness and stable links as the UAV moves through three-dimensional space.

Wireless propagation at low altitudes is strongly affected by the surrounding city. Buildings may block a link, while vehicles, pedestrians, and other moving objects can alter the propagation conditions over short time scales. A UAV link may therefore alternate rapidly between line-of-sight (LoS) and non-line-of-sight (NLoS) conditions, often with large changes in attenuation. The problem becomes more pronounced at millimeter-wave and sub-terahertz frequencies because penetration losses are higher and

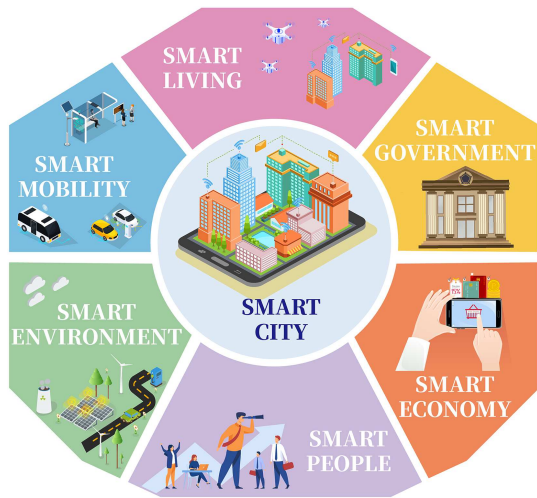
narrow beams are easily disrupted by blockage or motion. Channel models for these environments must therefore account for both the physical surroundings and their temporal variation. The resulting channel information must also be connected to antenna adaptation and communication control.

Communication needs vary across smart-city applications. Of the six domains illustrated in Figure 1, this review considers three in detail: Smart Mobility, Smart Living, and Smart Economy. UAVs used in these domains operate for different purposes, but all must exchange data while moving through low-altitude urban space. Safety requirements add a further constraint, particularly when communication delays or interruptions can affect flight decisions.

Traffic monitoring is a typical Smart Mobility application of UAVs and may form part of an intelligent transportation system [5]. Because the collected video and sensor data are often processed in real time, the communication link must provide sufficient capacity with limited delay and appropriate security protection [6, 7]. Smart Living applications include emergency response and medical-supply delivery [8]. Communication failures in such missions may delay assistance or prevent critical information from reaching its destination. For autonomous logistics and e-commerce delivery in Smart Economy [9], connectivity is needed throughout the flight to exchange operational data and manage the UAV trajectory [10, 11].

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Figure 1
Representative smart-city domains and typical application scenarios relevant to low-altitude UAV communications



The importance of each communication requirement depends on the application. Video-based traffic monitoring places considerable demand on data rate, whereas emergency and delivery missions are especially sensitive to delay, link failure, and security risks. Taken together, these cases explain the scope of this review, which covers urban channel characterization, adaptive antenna and material design, and algorithms for communication control and optimization.

Previous reviews have considered UAV networks, channel models, reconfigurable intelligent surfaces (RIS), or AI-based communication methods, usually as separate topics. Table 1 summarizes their coverage and positions the present review in relation to them.

Table 1 shows that the existing surveys usually emphasize one research direction at a time. This scope is useful for detailed treatment of individual methods, but it makes it harder to compare how channel conditions, antenna choices, and communication algorithms interact in a low-altitude smart-city network.

The existing literature leaves several issues unresolved. Channel models, antenna architectures, and communication algorithms are usually assessed separately rather than as interacting components of the same UAV system. Studies of low-altitude operation also tend to consider dense urban propagation, time-varying blockage, heterogeneous infrastructure, and application requirements in isolation. In addition, laboratory and simulation results are not always discussed in relation to deployment constraints, especially size, weight, power, and cost (SWaP-C), experimental validation, and standardization.

Accordingly, the literature is discussed along three lines: urban channel characterization, advanced antenna technologies, and intelligent communication optimization. For each area, attention is given to the method used, the operating scenario, the basis of evaluation, the reported improvement, and the limitations stated by the authors. The available evidence is uneven. Some findings have been supported by measurements or repeated evaluation, whereas others are difficult to compare because the underlying scenarios and assumptions differ. Much of the remaining work concerns measurement, hardware implementation, and system-level validation under realistic deployment conditions for Smart City Skyways.

Table 1
Comparison of representative works related to 6G-enabled UAV communications

Representative survey	6G vision	UAV communications	Urban channel characterization	RIS/metamaterials	AI-enabled communications	Smart-city perspective	Integrated review scope
[1]	✓	Δ	Δ	×	Δ	✓	×
[12]	×	✓	Δ	×	×	Δ	×
[13]	×	✓	✓	×	×	×	×
[14]	×	×	×	✓	×	×	×
[15]	×	×	×	✓	×	×	×
[16]	Δ	✓	×	×	✓	×	×
Ours	✓	✓	✓	✓	✓	✓	✓

Note: ✓ indicates comprehensive coverage of the topic; Δ indicates partial discussion; × indicates that the topic is not explicitly addressed.

2. Channel Characterization and Modeling in Urban Environments

2.1. Propagation characteristics of common building materials in outdoor environments for 6G

The development of outdoor 6G UAV communication systems requires a more detailed description of how common building materials interact with electromagnetic waves at millimeter-wave and terahertz (THz) frequencies. Frequency bands around 220 GHz and 340 GHz offer very large bandwidths and may support extremely high data rates, but they are also more sensitive to surface roughness, material composition, and small changes in the propagation geometry [11]. Studies of concrete, brick, glass, and wood have shown that surface irregularities and material heterogeneity increase diffuse scattering when the surface is illuminated by THz waves [17, 18]. As a result, a smaller fraction of the incident energy contributes to coherent reflection, which can reduce the received signal strength and alter the multipath structure. This effect is particularly relevant to low-altitude UAV links because the elevation angle, horizontal position, and relative orientation of the UAV can change continuously during flight.

The reflection and transmission behavior of a material is also determined by the operating frequency and the polarization of the incident wave. Measurements across several frequency bands indicate that, as the carrier frequency increases from the mmWave region toward the lower THz band, reflection loss tends to decrease in some configurations while transmission loss increases [19]. The difference between transverse-electric and transverse-magnetic polarization becomes more pronounced at oblique incidence angles, where the two polarizations can produce different reflected power levels [20]. These observations have two implications for urban UAV modeling. First, a material entry obtained at one frequency should not be transferred directly to another band. Second, antenna polarization and incidence angle should be included when evaluating propagation in street canyons or near building facades. Ignoring either factor can lead to an incorrect estimate of the reflected and transmitted components of the UAV channel.

A reliable THz propagation model therefore depends on accurate estimates of the relative permittivity (ϵ_r) and loss tangent ($\tan \delta$) of the materials encountered by the wave. The free-space method is a nondestructive technique in which the reflection and transmission coefficients of a sample are measured and then used to recover its electromagnetic parameters [21]. The Nicolson-Ross-Weir method remains a conventional approach for this extraction task, but phase ambiguities can reduce its stability when the sample is thick or highly lossy. Nonlinear least-squares fitting has been introduced as an alternative or complementary procedure for improving the agreement between measured coefficients and the material model [22]. The choice of extraction method consequently affects the parameters used in later ray-tracing or channel-simulation studies. This link between measurement uncertainty and channel prediction should be considered when results obtained from different material databases are compared.

Table 2 does not assign universal constants to the listed materials. Instead, it gives ranges that can serve as reference values in practical modeling. Under the ideal-metal approximation, a metal is represented as a perfect conductor with extremely large relative permittivity and zero loss tangent. This assumption produces very high transmission loss. Real metals depart from this approximation because their conductivity is finite, and differences in surface roughness alter the balance between reflection and absorption. The available marble values are less certain, as measurements at individual sub-THz frequencies are still limited. Ceramic properties also vary with composition, porosity, fabrication method, and surface finish.

For a site-specific channel model, these variations cannot be ignored when electromagnetic properties are assigned to particular walls or other surfaces. A generic material classification may conceal such differences. Surface roughness presents a related problem at sub-THz frequencies: it affects diffuse scattering and absorption, but few studies provide quantitative roughness data. Additional measurements would be useful, particularly if the material description and test conditions were reported in a consistent form. Any value taken from Table 2 should therefore be used under the frequency, material, and environmental conditions for which it was obtained, rather than assigned to all surfaces made from the same nominal material.

Table 2
Key electromagnetic parameters for common building materials

Materials	Common thickness	Relative permittivity	Loss tangent	Transmission loss	Surface roughness	Key uncertainty	Refs.
Concrete	5~30 cm	6.2~7.0	0.05~0.1	High	Rough, heterogeneous	Moisture content	[23, 24]
Glass	0.5~1 cm	5.0~7.0	0.01~0.02	Moderate	Smooth, homogeneous	Coating thickness	[24, 25]
Brick	10~20 cm	3.5~5.0	0.03~0.1	High	Rough	Surface aging	[26, 27]
Wood	1~5 cm	1.5~2.0	0.002~0.05	Moderate	Variable (smooth to rough)	Natural variability	[28, 29]
Marble	1~3 cm	8.5~9.5	0.02~0.04	Low-to-moderate	Polished, smooth	Limited data	[26]
Ceramics	0.5~2 cm	6.0~9.0	0.01~0.05	Low	Smooth to moderately rough	Composition	[30, 31]
Metal	0.5~2 cm	∞	0	Very high	Finish-dependent (polished/rough)	Surface finish	[28]

2.2. Dynamic blockage effect modeling methods

Dynamic blockage occurs when a pedestrian, vehicle, UAV, or another transient object interrupts a propagation path. The effect is particularly severe at millimeter-wave (mmWave) and terahertz (THz) frequencies, where a human or vehicle can cause abrupt attenuation of approximately 20–40 dB and can also increase retransmission or latency requirements [32, 33]. The problem becomes more difficult in dense networks that combine terrestrial base stations (BSs), aerial platforms, and RIS because several links may be affected by related blockage events. A useful model must therefore describe not only the average attenuation but also when the blockage occurs, how long it lasts, and whether nearby links experience correlated interruptions. This section compares statistical, geometric, sensor-assisted, and machine learning (ML)-based approaches according to these requirements.

Early studies commonly represented blockage with probabilistic state-transition models. Markov formulations describe a link as moving between LoS and NLoS states. Alsaleem et al. [34] assigned attenuation values to small blockers and estimated the transition probabilities from the propagation geometry. This formulation is relatively simple and can be useful for initial coverage analysis, but its accuracy depends on how well the chosen states represent the actual blocker distribution. In particular, a small number of independent states may not capture spatially correlated blockages in a crowded urban scene. A different abstraction was used by Baccelli et al. [35], whose user-centric cascade model analyzes coverage through the Laplace transform of aggregate interference. The two approaches address different questions: the Markov model emphasizes temporal state changes, whereas the cascade model emphasizes the joint effect of multiple blocking events on coverage.

Sensor-assisted methods provide information about the environment before a blockage is observed directly in the received signal. Charan et al. [36] used convolutional neural networks (CNNs) to process RGB camera data and reported 86% accuracy for the evaluated LoS disruption prediction task. LiDAR-based approaches use three-dimensional observations of the surrounding

scene and apply learning models to estimate whether an obstruction will enter the propagation path. Wu et al. [37, 38] reported prediction horizons of approximately 100 ms and accuracy of up to 95% in their evaluated settings. Radar provides a complementary source of information when optical sensing is unreliable. Demirhan and Alkhateeb [39] combined radar observations at a BS with a neural network trained on measured reflections from moving objects. Taken together, these studies suggest that sensing may allow the link to be adapted before blockage occurs. The improvement reported in each case, however, depends on the quality of the sensor data, the training set, the weather conditions, and the geometry of the deployment.

Dynamic ray tracing provides a different way to describe changing blockage by updating the propagation scene as objects move. Liu et al. [40] introduced moving scatterers into conventional ray-tracing models to represent the rapid channel variations expected in 6G environments. Recalculating a complete visibility matrix whenever the scene changes can be costly. The methods in [41, 42] reduce this cost through preprocessing and dynamic visibility checks, so that the calculation is concentrated on obstructions that have appeared, disappeared, or changed position. Their results show that this selective update can shorten the computation while preserving the required accuracy. Such updating is useful in urban environments, where a largely static building layout is continuously modified by the movement of vehicles and pedestrians [42].

Table 3 summarizes how representative blockage models describe the channel, what environmental data they use, and how much computation they require. It also considers whether they can follow the changes encountered by a 6G UAV link. An overall accuracy ranking would be misleading because the models have different purposes and have not been tested under the same conditions.

Statistical models are inexpensive to run and fit naturally into system-level simulations. Because they contain little geometric detail, they may not reproduce blockage events that are correlated across nearby links or successive time steps. Ray tracing gives a more explicit account of buildings, reflections, and moving scatterers. This detail requires a three-dimensional map,

Table 3
Comparative summary of dynamic blockage models and 6G-specific challenges

Model	Strengths	Limitations	Recommended 6G scenario	Refs.
Markov chains	Simple framework for LoS and NLoS state transitions	Data dependency; struggles with accurately modeling complex spatial correlations in dynamic environments	Large-scale IoT planning	[34]
Cascade models	Capable of capturing joint blockage effects and dependencies; useful for understanding interference	High computational complexity; may not be practical for real-time decisions in dynamic contexts	Network performance analysis	[35]
Vision/LiDAR/Radar	High prediction accuracy and provides real-time monitoring capabilities	High costs for hardware and sensitive to environmental conditions; privacy concerns may arise	Real-time UAV navigation	[36–39]
Visibility pre-processing ray tracing (RT)	Enhances ray-tracing methods by reducing computational complexity while maintaining accuracy	Effectiveness depends on the availability of accurate and up-to-date static maps	Digital Twin-enabled urban UAV delivery	[43]

together with repeated calculations when the scene changes. Cameras, LiDAR, and radar provide more immediate information about nearby obstacles and may indicate that a link is about to be blocked. Their use adds sensors and calibration to the platform, and the observations may be less dependable in rain, fog, or poor lighting.

These approaches can serve different stages of the same analysis. A statistical model can represent blockage across a large network, ray tracing can resolve the propagation paths at a particular site, and onboard sensors can follow changes over the next few moments. The useful combination depends on the required prediction time, the environmental information already available, the time allowed for control, and the onboard computing resources.

2.3. Empirical UAV channel measurements and testbed validation

Theory and simulation do not reproduce every feature of a measured UAV channel. In a field campaign, the receiver records the signal, while the UAV or ground terminal moves through the test area. Path loss, reflections, blockage, antenna orientation, and platform motion are therefore present in the same dataset rather than introduced separately. The measurements provide a direct check on modeled urban links. They can also reveal how the channel changes with altitude, frequency, street layout, and nearby objects. If the measured and modeled results disagree, the assumptions responsible for the difference can be reconsidered before the model is used in deployment planning.

The examples below span several frequency bands and urban settings. Fuschini et al. [44] collected street-canyon measurements using a UAV equipped with millimeter-wave (mmWave) and ultra-wideband (UWB) transceivers. Their dataset describes path loss, angular spread, and reflection effects and can be used to calibrate or test ray-based propagation models. In an earlier study, Yang et al. [45] measured UAV air-to-ground channels in an urban campus environment. The reported path-loss exponents, K-factor variations, and root mean square (RMS) delay spreads showed how the channel changed with altitude and blockage conditions. Li et al. [46] investigated a ground-to-UAV link at 140 GHz and reported sub-terahertz measurements related to power decay, beam-alignment sensitivity, and fluctuations during hovering. Although each campaign adds useful evidence, the reported values are tied to a particular experimental setup. Differences in antennas, flight paths, and local geometry prevent a direct numerical comparison across studies.

Table 4 records the platform, frequency band, test environment, measured quantities, and main result of each campaign. The experiments answer somewhat different questions. Measurements in street canyons are useful for studying reflections and angular spread. Campus trials provide more information on changes with altitude and on blockage, whereas sub-terahertz experiments show the effect of motion and beam misalignment on narrow-beam links. Coverage is still uneven. In particular, public measurement data are scarce at higher frequencies, and little is available for RIS-assisted UAV links. Future datasets would be more useful if they included the actual flight path, antenna orientation, and blockage state alongside time-synchronized channel measurements. These records would allow other researchers to repeat the analysis and determine whether the resulting models remain valid at a different site.

2.4. Critical evaluation and future research directions

The three approaches discussed above answer different questions about an urban UAV channel. Material characterization describes how a surface changes the amplitude, phase, polarization, and scattering of an incident wave. Dynamic blockage modeling describes how the channel changes when pedestrians, vehicles, or other objects move through the propagation path. Empirical campaigns test whether the assumptions used in the first two approaches remain valid under an actual flight trajectory and urban geometry. These roles are related but should not be treated as interchangeable. Material properties provide parameters for ray-tracing and statistical channel models. As the surrounding scene changes, a blockage model describes how the channel is updated, while measurements provide a basis for calibrating both the material parameters and the assumed blockage process. These three parts need to be considered together. A detailed model in one part cannot correct for poorly characterized materials, unrealistic blockage assumptions, or limited field measurements elsewhere in the workflow.

Statistical blockage models use only a small number of state variables and are inexpensive enough for coverage studies, network-level simulations, and preliminary resource allocation over a large area. The drawback lies mainly in how blockers and their movement are represented. Assumptions of a uniform spatial distribution, independent blockage events, and constant or slowly changing transition probabilities become questionable when pedestrians move in groups or vehicles follow the same traffic flow.

Ray tracing retains the geometry of the physical scene and can account for reflection, diffraction, and the way blockage

Table 4
Representative UAV channel measurement campaigns

Reference	Frequency band	UAV platform and scenario	Environment	Key findings
[44]	mmWave and UWB	UAV-ground setup	Urban street canyon	Validated ray-based models; measured path loss, angular spread, and reflections
[45]	Sub-6 GHz (2.4GHz)	UAV flights on campus	Urban (Tsinghua Univ.)	Derived path-loss exponent, K-factor, RMS delay spread; highlighted altitude/blockage sensitivity
[46]	140 GHz (sub-THz)	UAV with horn antenna	Outdoor ground-UAV link	First sub-THz UAV dataset; beam-alignment sensitivity and hovering-induced fluctuations

interacts with nearby buildings. Its use depends on an accurate three-dimensional map, and repeated scene updates can be computationally expensive. Sensor-assisted methods work differently. Rather than waiting for the received signal to deteriorate, they use current observations to identify an obstruction that is moving toward the link. In the scenarios studied, prediction accuracy has approached 95% for horizons of about 100 ms. Whether this performance carries over to another deployment depends on the sensors, training data, weather, and local geometry. Practical implementation also requires the sensing hardware to be installed, calibrated, and synchronized with the communication system, while the sensor data must be stored and processed. A method should therefore be judged not only by its reported accuracy but also by the environmental detail and prediction time it provides for a given computing and integration cost.

Which channel-characterization method is useful depends on the task. A statistical model is often sufficient for coverage planning or for comparing several network layouts, especially when a detailed map is not available. Infrastructure design, street-canyon analysis, and Digital Twin development usually need more spatial detail. Ray tracing can provide it if the underlying three-dimensional city model is accurate and regularly updated. Sensor data become more useful when the environment changes over short time scales. For low-altitude navigation, autonomous delivery, or urban air mobility, predicting an obstruction a short time in advance may be enough to switch a beam, change a route, or select another link.

A hybrid system can divide this work among several models. The statistical component gives a quick estimate across the network, ray tracing resolves propagation around a particular site, and sensors follow recent changes near the UAV. Detailed prediction then runs only where and when it is needed. The difficulty is that outputs produced at different scales and update rates must still agree. Data fusion and timing errors may otherwise offset the gain in prediction accuracy. These implementation issues need to be included when the hybrid system is evaluated.

The evidence is particularly limited above 100 GHz. Existing measurements do not yet show whether the same material parameters and propagation models apply to different buildings, weather conditions, or flight paths. Evaluation of hybrid blockage models is also incomplete. Many studies demonstrate a working prototype but relatively few test the statistical, deterministic, and sensor-based components together using the same data and protocol.

Learning-based prediction raises a separate issue. A model may achieve a lower prediction error while producing channel behavior that is inconsistent with electromagnetic constraints. Adding physical constraints to the learning process could reduce this inconsistency, but suitable training and evaluation require paired measurements and a clearly defined test procedure. Digital Twin updates face a related reproducibility problem. They require common data formats, simulation interfaces that can exchange information, and benchmarks that can be repeated outside the original test platform.

Future reports should include the measurement conditions, blockage labels, update interval, computational cost, and validation procedure, not only the final prediction score. With these details, an improvement can be traced more reliably to the method itself rather than to a favorable dataset or test site.

3. Antenna System Design for Urban 6G

Blockage and UAV motion continually change the geometry of an urban wireless link. Antenna control must follow these

changes, but the hardware carried by the UAV remains constrained by weight and available power. RIS and metamaterial antennas address this problem at different points in the link. An RIS redirects the incident wave through changes made in the surrounding propagation environment. A metamaterial antenna instead changes the radiation produced or received by the communication node itself. The two subsections below consider the coverage and beam-control capabilities of each approach, together with their power demand, cost, and implementation constraints.

3.1. Reconfigurable intelligent surfaces (RIS)

RIS are programmable electromagnetic metasurfaces that can dynamically control incident radio waves [47]. As an enabling technology for 6G wireless networks, RIS can help address the limitations of urban low-altitude UAV links, where moving blockages and severe multipath fading reduce signal reliability. By reconfiguring the propagation environment, RIS can support more reliable communication along Smart City Skyways [14].

A generic RIS-assisted communication link models the received signal at the UAV. This signal, y_{UAV} , is from cascaded channels from the BS to the RIS and then from the RIS to the UAV:

$$y_{UAV} = (h_{RIS-UAV}\Phi H_{BS-RIS} + h_{BS-UAV})x + n \quad (1)$$

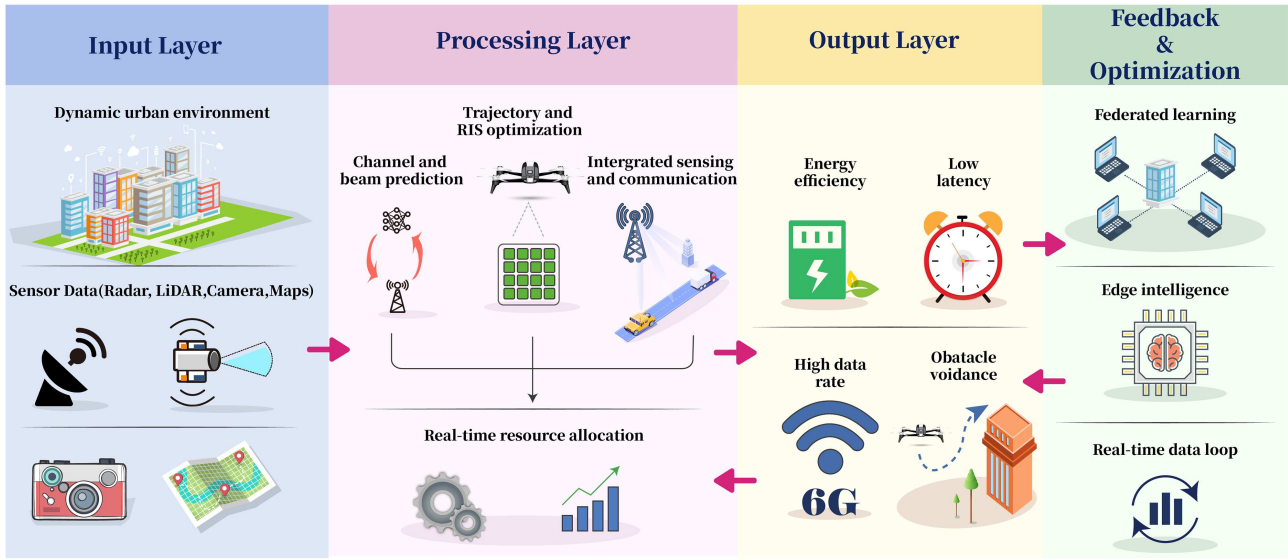
Here, y_{UAV} is the received baseband signal at the UAV, and x is the transmitted signal vector. The term H_{BS-RIS} represents the channel matrix between the BS and the RIS, which is modeled as a matrix because both ends typically involve multiple antennas or reflecting elements, resulting in a multiple-input multiple-output (MIMO) channel. The vector channel $h_{RIS-UAV}$ represents the RIS-UAV link; since the UAV is usually equipped with a single antenna, this reduces to a vector describing one effective channel coefficient per RIS element. The direct BS-UAV channel is denoted by h_{BS-UAV} , which may be absent or severely attenuated in urban environments. Φ is the diagonal RIS phase shift matrix (unit modulus for passive RIS; per-element amplitude and phase for active RIS), and n is the additive white Gaussian noise with $n \sim \mathcal{CN}(0, \sigma^2)$. This model has been widely adopted in RIS-assisted communication studies [48].

This formulation separates the direct path from the RIS-assisted reflection path. By adaptively tuning the RIS phase shifts, the reflected components can be coherently combined at the UAV so that multipath signals add constructively. This improves the received signal-to-noise ratio (SNR) and can even create a virtual LoS channel when the direct path is blocked. Thus, RIS does not amplify transmit power but enhances communication quality by intelligently reshaping the propagation environment.

Figure 2 illustrates an urban UAV scenario in which a building-mounted RIS provides an indirect communication path when the direct path is obstructed. This arrangement is relevant to applications such as real-time traffic monitoring and emergency response, where the UAV must remain connected while moving through an urban canyon. The additional path can improve throughput and reduce latency under these changing conditions.

Passive, active, and centralized active RIS designs differ mainly in the gain they provide and the cost of providing it. A passive RIS changes the phase of the incident signal without radio frequency (RF) amplification. Its power demand is low, the hardware is comparatively simple, and a large number of elements can be deployed over a wide area. The absence of amplification also limits its performance. In a cascaded BS-RIS-UAV link, the

Figure 2
Representative ecosystem of RIS-assisted urban UAV communications, illustrating the interactions among urban propagation environments, adaptive antenna technologies, and representative smart-city applications



signal experiences multiplicative fading, which can reduce the RIS gain when the path is long or heavily blocked. Under the system configuration evaluated in [49], the passive RIS improved link performance by approximately 22%.

An active RIS places amplifying components within the reflecting elements to recover part of the cascaded path loss. The study in [49] reported considerably higher sum rates than those obtained with a passive RIS. This improvement came with additional power consumption, amplified noise, and more complicated hardware. A passive design is consequently a practical choice when energy use and deployment scale are the main concerns. Active elements become more attractive when the additional link gain is worth their power and hardware cost.

How the RIS is tuned also matters in practice. Passive surfaces generally use PIN diodes or varactors to select among discrete phase states. Active and centralized active designs must coordinate phase control with amplification. When the urban channel or UAV trajectory changes quickly, AI-based methods such as deep reinforcement learning (DRL) can be used to update the phase configuration [15, 50].

Phase control depends on knowledge of both the BS-RIS and RIS-UAV channels. Obtaining this channel-state information (CSI) becomes harder as the number of reflecting elements increases. The cascaded form of the channel and the absence of active RF chains on most RIS elements also make direct observation difficult [51]. Proposed solutions use compressed sensing [52], tensor or matrix factorization [51], and deep learning [53]. For a moving UAV, position data and observations of the surrounding environment may provide additional information for predicting the channel and link quality [54].

These estimation methods can lower pilot overhead, but their effectiveness is tied to assumptions about channel sparsity and model accuracy, as well as the quality of sensing and training data [51]. UAV motion creates a further difficulty by shortening the channel coherence time. In an urban millimeter-wave or terahertz link, channel estimation and RIS phase updates may then need to be completed within a very short interval [51, 54]. One possible direction is to combine low-overhead pilots with location

and sensing information, while predicting the channel jointly with RIS control [51].

RIS deployment still faces hardware and coordination limits. Errors in synchronization across the elements, nonideal circuit behavior, and reflection losses can reduce both link reliability and overall system performance.

Signals reflected by different RIS elements combine coherently only when their phases are accurately synchronized. This condition is difficult to maintain in a multipath channel because channel variation, oscillator offset, and delay in the control link can shift the element phases and produce destructive interference. Synchronization has been approached through hierarchical control, distributed phase calibration, reference signals, and phase tracking based on predicted channel changes. These techniques reduce the amount of repeated calibration, but their performance can deteriorate as UAV speed and control latency increase. Coordinating a large surface introduces a further scaling problem [55].

The behavior of a practical RIS also differs from that of an ideal surface. IQ imbalance, phase noise, nonlinear amplification, finite phase resolution, and mutual coupling distort the signal or prevent the intended phase shift from being applied accurately. The resulting loss appears in both spectral and energy efficiency [56–58]. Proposed solutions range from low-resolution phase shifters and element grouping to hardware-aware beamforming, impairment compensation, and energy-efficient active or semi-active designs [59–61]. Simpler hardware does not remove the need for an accurate impairment model. Calibration, power use, and fabrication cost may also increase, depending on how the compensation is implemented.

A further loss arises when the RIS elements do not reflect the incident signal as intended. Their effective reflectivity changes with fabrication tolerances, incidence angle, polarization, frequency, and operating environment. The beam may then deviate from its desired pattern, with a corresponding reduction in link gain [59, 62, 63]. Wideband unit cells, impedance matching, polarization-aware control, and better RIS placement can limit this loss. Active or hybrid surfaces may also compensate when the

cascaded path is too weak. Achieving high reflectivity over a wide bandwidth and a rapidly changing range of incidence angles is still difficult, especially at millimeter-wave and THz frequencies.

RIS can improve UAV links in urban areas, but the achievable gain depends on more than phase optimization in an ideal channel. Synchronization, circuit impairments, and reflection losses must all be included in the design and evaluation. Progress in materials, control hardware, and adaptive signal processing will determine whether RIS can be used reliably in Smart City Skyways.

3.2. Metamaterial antennas for urban integration

Metamaterial antennas use engineered sub-wavelength structures to control their effective permittivity and permeability. This control enables compact antenna designs with adjustable beams and increased gain, which is useful when a UAV has limited space and payload capacity. Some structures can also exhibit a negative refractive index and provide wavefront control that is difficult to achieve with conventional antennas [64, 65].

The reported gain improvement can be substantial. Conventional microstrip antennas in the cited studies achieved gains of about 7.46 dB, whereas the corresponding metamaterial designs exceeded 12 dB, with increases of up to 50% [66, 67]. Higher gain is particularly useful on a UAV, where the available transmission power is limited.

Miniaturization is another reported benefit. Antenna dimensions have been reduced by 50% or more in some designs without a corresponding loss of performance. Sub-wavelength structures make this possible by changing the effective electromagnetic properties of the antenna. Split-ring resonators, for example, can lower the operating frequency of a compact structure [68]. The reduced antenna size makes integration easier when only a small area is available on the UAV.

Beam control varies with the metamaterial design. Some antennas can scan over 180 degrees and provide nearly complete coverage in azimuth and elevation [69]. This range allows the beam to follow a moving UAV or maintain a link as its orientation changes in an urban environment.

Bandwidth improvements typically range from 30% to more than 100% over conventional designs. Expansions of up to 220 MHz have also been reported, supporting multiband communication and different wireless protocols [70, 71]. This broader frequency operability is useful for systems with multiple communication bands.

Fabrication and materials advances have reduced the cost of metamaterial antennas. A more complicated antenna is not necessarily more expensive over its full operating life. For metamaterial designs, the additional fabrication cost may be recovered through lower energy use or functions that would otherwise require several separate components [72, 73]. This trade-off is becoming more relevant as UAV platforms demand smaller antennas with multiple operating modes.

Additive manufacturing has been used to produce low-cost Luneburg lenses with beam-scanning capability for UAVs [74]. Wide-angle scanning arrays can serve users from a UAV-mounted BS [75], while hybrid designs have been developed for platforms with tight cost and payload limits [76]. Synthetic metasurfaces that can be produced by three-dimensional printing allow the antenna shape to be adapted to the UAV body or its urban surroundings [77]. At THz frequencies, three-dimensional-printed lenses [78] and tunable metasurfaces [79] provide beam steering that can follow changes in the link geometry.

The measured response of a fabricated antenna may differ from that predicted for its ideal geometry. Variations in unit-cell dimensions, substrate properties, and material losses can shift the resonant frequency or distort the beam pattern. These effects become more pronounced at millimeter-wave and terahertz frequencies [80]. The antenna also experiences vibration, changing temperature and humidity, ultraviolet exposure, and mechanical loading during UAV operation. Over time, these conditions can alter its structure and electromagnetic response [81]. Better consistency has been reported with additive manufacturing, precision lithography, low-loss dielectrics, and flexible metasurfaces [74, 77, 82]. The remaining difficulty is to reproduce the same electromagnetic response across many low-cost units, rather than only in a small number of prototypes.

Where a conventional antenna already meets the link requirement, the additional complexity of a metamaterial design may offer little benefit. The case is stronger when installation space is limited, the antenna must conform to the platform, or the beam must be redirected electronically. Similar size and conformability requirements arise in wearable monitoring, where the antenna is integrated close to the body [64, 68]. On a UAV, a smaller and lighter antenna leaves more capacity for batteries, sensors, or other payloads and may improve both flight and communication performance [73]. Beam steering can also follow changes in the flight path or redirect the link around a moving obstacle [71].

The reported advantages over conventional antennas include greater gain, smaller dimensions, and wider bandwidth. For an urban UAV, these properties are most useful when they are obtained together with controllable radiation and a form that can be integrated into the airframe. Large-scale use will depend on whether manufacturers can reproduce that performance in lightweight antennas without making fabrication prohibitively expensive.

3.3. Performance indicators for urban 6G antenna systems

RIS and metamaterial antennas act on different parts of an urban UAV link. An RIS changes the path between the transmitter and receiver by controlling reflections in the surrounding environment. A metamaterial antenna changes the radiation produced or received at the communication node. The two technologies therefore differ in coverage, power consumption, cost, and ability to follow changing link conditions. Table 5 places these differences side by side for different deployment needs.

An RIS is useful when a building or another obstacle blocks the direct path. By setting the reflection pattern, the surface can direct more of the incident energy toward the receiver and extend coverage beyond the obstruction [83, 84]. A metamaterial antenna instead steers the beam from the communication node. The reported scanning range depends on the antenna, with some designs reaching $\pm 30^\circ$ or more [85, 86]. Composite right/left-handed structures achieve this scanning electronically and do not require mechanical movement [87]. They can therefore adjust the beam as a UAV moves or maintain a directed link with an on-body device.

Power use presents a further difference. A passive RIS redirects the signal without RF amplification and can reduce the transmission power needed at the BS [84]. The resulting system-level power saving may help extend UAV operating time, including during missions in GPS-denied environments. Metamaterial antennas obtain their gains mainly through higher directivity, but real-time beam adaptation may require more

Table 5
Comparative analysis of RIS and metamaterial antennas for UAV networks

Feature	RIS	Metamaterial antennas	Complementarity
Primary function	Manipulates and reflects incoming waves to enhance signal strength and create virtual LoS paths	Actively radiates and receives signals with superior properties, such as higher gain and efficiency	RIS reshapes propagation; metamaterial improves radiation
Deployment	Static surfaces integrated into the urban infrastructure (e.g., building facades, walls, banners)	Onboard integration onto the UAV itself due to their compact size and lightweight nature	Infrastructure + onboard cooperative deployment
Coverage	Extends network coverage by overcoming blockages and enabling communication in NLoS scenarios like urban canyons	Increases the direct communication range for single-hop links due to enhanced gain and efficiency	RIS extends coverage; metamaterial strengthens local links
Energy	Passive or semi-passive; requires very low power for configuring the reflection elements	Active elements that require power for signal processing and radiation	Passive environmental control + efficient beamforming
System cost	Lower cost per element, but can be expensive for large-scale urban infrastructure deployment	Can be more costly than conventional antennas due to complex design and fabrication processes	Infrastructure investment balanced by onboard flexibility
Integration	External to the UAV, serving as part of the surrounding environment's infrastructure	Directly integrated onto the UAV's airframe, occupying a minimal footprint	Joint infrastructure–platform architecture
Flexibility	Semi-dynamic; while configuration can change, the physical location of the surface is fixed	Dynamic; can be used on a mobile platform to provide superior radiation characteristics while the UAV is in flight	Environmental adaptation + platform adaptation
Application scenario	Ideal for providing connectivity in dense urban areas where direct links are often obstructed	Best for maximizing signal quality and range for high-speed, single-hop data transfer	Hybrid smart-city UAV communication

signal processing and power [88]. RIS is therefore generally more efficient when minimizing power consumption is the main objective.

RIS can also be cost-competitive because passive deployment requires few active components and reduces operating overhead [84]. Metamaterial antennas may cost more to manufacture because of their intricate sub-wavelength structures, although advances in fabrication are lowering production costs [88]. Their higher initial cost may nevertheless be justified in high-stakes applications when the resulting performance is important to the deployment.

Reconfigurability allows a metamaterial antenna to change its radiation characteristics for different tasks and operating environments. This is useful in on-body communication, where the antenna must remain functional while conforming to the shape and movement of the wearer [88]. The same properties support compact and lightweight installation on UAVs and wearable devices. An RIS is reconfigurable in a different sense. Once the surface has been installed, adaptation is normally achieved by changing the states of its elements; the physical shape and position of the surface generally remain fixed.

The intended application determines which form of reconfiguration is more useful. An RIS is suited to low-power signal redirection and coverage improvement across a large urban area, particularly when several users or UAV links share the same

environment. A metamaterial antenna is more appropriate when the antenna must be small, conformal, and capable of directing its beam from the communication node. The two technologies may also operate in the same link. In that case, the RIS shapes the external propagation path, while the metamaterial antenna controls transmission or reception at the node. Such a design may be useful in dense urban areas where both limited coverage and platform integration constrain the link.

These differences can also be viewed through specific smart-city applications. An RIS may help urban air mobility or emergency-response UAVs maintain a link when buildings block the direct path. For aerial logistics and infrastructure inspection, a lightweight metamaterial antenna can provide onboard gain and directional control without occupying much space. Antenna selection should therefore reflect the communication task, the platform constraints, and the propagation conditions at the deployment site.

3.4. Performance indicators for urban 6G antenna systems

RIS and metamaterial antennas perform different functions in an urban 6G aerial network and can be used together. The RIS controls part of the propagation path, while the metamaterial antenna adjusts radiation at the transmitting or receiving

node. A hybrid system can use both forms of control rather than selecting one technology to replace the other.

The practical limits are also different. RIS can improve coverage and reduce energy use, but the achievable gain depends on where the surface is installed, how accurately the CSI is estimated, and whether its elements remain synchronized. Metamaterial antennas can provide high gain, rapid beam adjustment, and a compact form. Their deployment, however, is affected by fabrication difficulty, manufacturing variation, and the ability of the antenna to retain its performance after long exposure to the operating environment.

Most studies examine the two technologies separately and assume propagation conditions that are more controlled than those encountered in a city. A deployed UAV link will require antenna design and propagation control to operate together with flight motion and the communication protocol. This combined behavior has received less experimental study, particularly at millimeter-wave and THz frequencies, where the available literature remains dominated by simulation.

Future studies should examine integrated RIS–metamaterial architectures, joint beam management and propagation control, AI-assisted adaptive antenna systems, and hardware-aware co-design subject to the SWaP-C constraints of UAV platforms. Such coordinated designs could support more scalable and reliable Smart City Skyways.

4. Intelligent Algorithms for Dynamic Environments

Section 4 turns to the algorithms used for channel prediction, beam management, trajectory control, sensing, and resource allocation in urban UAV networks. Figure 3 follows the processing chain from sensing and perception to algorithmic decision-making and then to communication or flight control. The stages are shown separately because they operate on different data, control different variables, and may run at different rates.

Table 6 classifies each reviewed method by its main role. ML methods are used for channel prediction and beam management, while RL addresses sequential decisions such as trajectory planning and RIS control. Resource allocation is also studied using classical optimization and metaheuristic algorithms. Federated and edge learning move model updates across distributed nodes without requiring all data to be processed at one location. Methods that combine sensing and communication use observations of the environment to guide communication decisions, although the two data streams must then be fused and coordinated.

For each method, the discussion asks what data it uses, what quantity it optimizes, how much computation it requires, and how it has been validated. These points cannot be separated from the task for which the algorithm was designed. A method developed around one objective and update rate may perform differently when applied to another control problem. The review therefore

Figure 3
A conceptual framework for an AI-enabled urban UAV network, illustrating the key functional modules and their interconnections

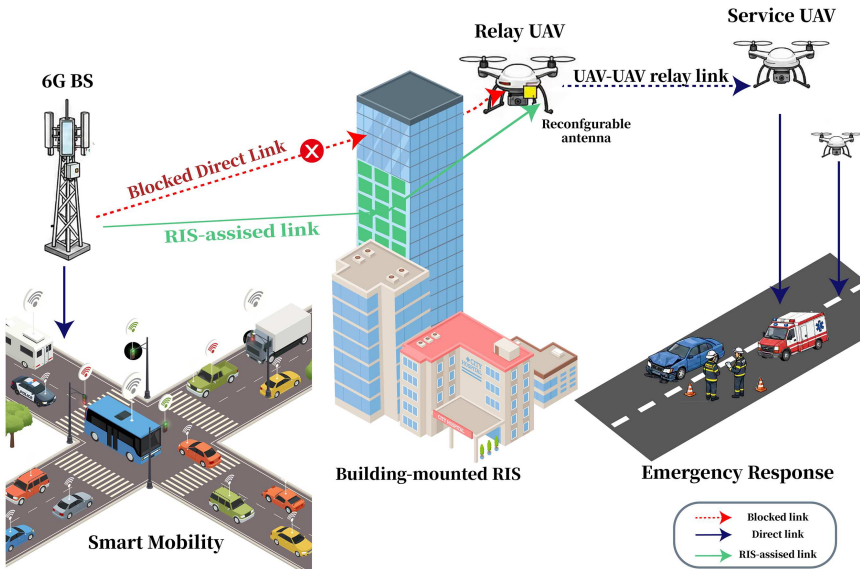


Table 6
Taxonomy of AI/ML algorithms for UAV networks

Category	Primary objective	Representative methods	Typical inputs
Sensing-centric	Maximize sensing accuracy/target detection	CNN, Transformer, multimodal fusion	LiDAR, camera, radar
Communication-centric	Maximize throughput/reliability/secretcy	DRL, supervised channel predictors, beam selection	CSI, traffic demand
Joint (sensing and communication)	Trade-off/balanced optimization	Multi-task deep learning (DL), MARL, constrained optimization + RL	Multimodal sensors + CSI + mission objective

does not treat any algorithm as a general solution for energy use, latency, throughput, and obstacle avoidance across all urban operating conditions.

4.1. Classical analytical and optimization methods

Classical optimization remains useful for UAV communication problems when the objectives and constraints can be written explicitly. The decision variables are interpretable, and many formulations can be solved with moderate computational effort. These methods are therefore commonly used as benchmarks for learning-based algorithms. In some cases, they also provide convergence guarantees or analytical bounds that are difficult to obtain from a black-box model. Their reliability, however, depends on the assumed channel, mobility, and traffic models. If these assumptions no longer match a rapidly changing environment, or if the resulting problem is highly non-convex, a tractable mathematical solution may not produce the best decision during operation.

Convex approximation, successive convex approximation (SCA), and fractional programming have been used for power allocation, trajectory planning, and spectrum management. One example is the Dinkelbach method, which has been applied to power allocation in heterogeneous networks [89]. Convergence can be rapid for suitable problem formulations. In the scheduling scenarios evaluated in [90], the reported convergence time was on the order of milliseconds. Such results depend on the number of variables, the channel information available to the optimizer, and the frequency at which the problem must be solved again. In a mobile UAV network, the computation time should therefore be compared with the channel coherence time and the delay required to obtain the relevant CSI. A fast solver is useful only when its solution remains valid long enough to guide the next communication or control action.

Heuristic and metaheuristic methods are useful when the problem is non-convex, combinatorial, or difficult to solve repeatedly with a deterministic procedure. Genetic algorithms (GA), particle swarm optimization (PSO), and ant colony optimization (ACO) can explore a large solution space without requiring a convex reformulation. This flexibility is valuable for routing and other discrete-decision problems, although these methods do not generally provide a guarantee of global optimality [91]. ACO-based studies have reported improvements in UAV routing efficiency under specified network and mobility constraints [92]. The result depends on the population size, stopping rule, objective weighting, and comparison baseline. Metaheuristic methods may therefore be useful for offline planning or for generating an initial solution, while a faster local procedure performs online updates.

Stochastic geometry is mainly used for large-scale UAV networks rather than for one specific flight path. By modeling the spatial distribution of UAVs, BSs, and interferers, it provides analytical descriptions of coverage probability, interference, and spectral efficiency [93]. This approach reduces the need for exhaustive simulation and is useful for system-level comparisons. Its conclusions, however, depend on the assumed spatial process, fading model, blockage model, and stationarity of the network. Studies applying stochastic-geometry analysis to UAV deployments have provided useful benchmarks under urban multipath conditions [94], but these averages do not directly describe the channel experienced by an individual UAV near a particular building or obstacle.

4.2. Machine learning for channel prediction and beam management

ML methods are used in urban UAV networks for channel prediction and beam management. The model is selected according to the input data and decision task: CNNs represent spatial features, LSTMs represent temporal sequences, and graph neural networks (GNNs) represent relationships among nodes in a wireless network.

CNNs can extract spatial correlations from geographic maps, received-signal-strength maps, and other high-dimensional representations of CSI, which is useful for spatially varying channels. LSTMs capture temporal dependencies and are useful when the channel changes as a UAV moves through the environment [95, 96]. GNNs describe UAVs and BSs as nodes and their communication links as edges. This representation retains the relationships among network entities and has been used for beam management in multi-UAV systems [97, 98]. GNNs may also be combined with other learning models, although the usefulness of doing so depends on the available data, the prediction horizon, and the resources required for inference.

ML can learn nonlinear channel relationships without reducing them to a small set of analytical assumptions. Conventional methods often use static fading models, simplified motion, or a search over many pilot signals. An ML model can instead map previous observations to a channel estimate or control decision [99]. It still needs channel-related information; the difference lies in how that information is processed. Once training is complete, inference may take less time than an exhaustive search. The cost of training and unreliable behavior outside the range of the training data remain significant limitations [100].

The numerical improvements reported in the literature depend on the dataset, baseline, and system configuration. Pilot overhead was reduced by as much as 82% in one 5G mmWave massive-MIMO study [101]. Another study reported a CSI-prediction error below 1 dB under its test conditions [102]. For a particular UAV scenario, predictive information produced a spectral-efficiency improvement of up to 250% [101]. These numbers describe different experiments. Their frequencies, channel models, baselines, training sets, and evaluation procedures are not the same, so they do not form a common benchmark for ML performance.

Running a deep learning model on a UAV or an edge server places demands on processing capacity, memory, and energy. Training can add substantial computation and data-transfer cost. Smaller models, compression, and edge inference can shorten the decision time, but the saving may come with lower accuracy or more communication between the UAV and the edge server. Algorithm performance and platform cost must therefore be measured under the same operating setup.

The strongest case for ML arises when the available records cover the channel states, mobility patterns, or beam decisions expected during operation. A model trained on one city layout or flight pattern may perform poorly after the blockage pattern, weather, or trajectory changes. Evaluation should account for this shift by reporting the coverage of the training data, the need for retraining, the inference delay, and performance outside the training distribution, rather than prediction accuracy alone.

4.3. Reinforcement learning for RIS and UAV trajectory optimization

Reinforcement learning (RL) treats UAV control as a sequence of decisions. At each step, the agent uses its observation

of the environment to choose an action and then receives a reward. This setup is relevant when the channel, UAV motion, and blockage evolve during operation and are difficult to describe with a fixed optimization model. By interacting with a simulated or measured environment, an RL agent can learn a policy for trajectory planning or RIS control in an urban network [103]. The learned policy need not enumerate every future state explicitly. Its performance, however, remains tied to the chosen state representation and reward function, as well as the training scenarios and interaction data.

For navigation, Deep Q-Networks (DQN) and related algorithms have been used to choose actions that account for energy consumption and latency within a Markov decision process (MDP) [104]. Reported studies have found energy efficiency gains of 55–80% over conventional schemes in their evaluated settings [105]. Multi-agent reinforcement learning (MARL) extends the formulation to UAV swarms, where agents must coordinate trajectories or share limited resources [106]. Compared with a static optimization solution, RL can update a policy as observations change, but the benefit depends on reliable state information and stable training.

RL can also update RIS phase shifts together with the UAV trajectory. The RIS changes the reflected path, while the UAV changes its position and viewing geometry; treating the two decisions separately may produce an inconsistent control sequence. Joint formulations have been used to adjust RIS parameters while guiding the UAV away from shadowed regions [107]. Reported studies include a 34% throughput increase and a 46.61% improvement relative to a non-learning baseline under particular configurations [108]. These values depend on the RIS size, channel model, baseline policy, and reward definition. Multi-agent methods have also been investigated for secure RIS-assisted UAV communication [109], although they increase coordination and training overhead.

The choice of RL algorithm depends on the action space and training budget. Value-based methods such as DQN are convenient for discrete actions but may require many samples. Policy-based methods, including Advantage Actor-Critic and Proximal Policy Optimization, suit continuous control but generally require more computation. Transfer learning can reduce the cost of training a deep RL policy. In experiments conducted on real maps, transfer-assisted training used 30–58% less energy and required up to about 47% fewer convergence steps than training from scratch [110]. The actor-critic-based deep stochastic online scheduling (AC-DSOS) method produced near-optimal solutions within milliseconds in its evaluated setting, while the conventional offline baselines required minutes [111]. The meaning of these gains depends on how the experiment was configured, including the training environment, stopping rule, and implementation of the baseline.

Several problems remain when an RL policy is moved from evaluation to an urban UAV. The agent may need to act before accurate CSI, obstacle positions, or mobility information is available. Errors in these observations can place the agent in an MDP state that does not represent the actual situation. Deep models can use sensory inputs and respond to channel changes [103], but a policy trained under one set of conditions may fail when the deployment environment falls outside that distribution.

Joint optimization of the trajectory and RIS configuration allows energy use, latency, and data rate to be considered in the same control problem [107]. It also increases the number of states and actions that the agent must explore. For large and nonstationary multi-agent systems, most deep RL methods offer limited convergence guarantees, so their performance is

established mainly through experiments. The outcome may change with the reward function, exploration strategy, training stability, and treatment of safety constraints. A deployment study should examine these factors alongside communication performance, particularly when the method is intended to scale to many UAVs.

4.4. Joint sensing and communication with AI-driven control

Joint sensing and communication (JSAC) places environmental sensing and communication-data transmission in the same system. This review uses integrated sensing and communication (ISAC) as the general term for such systems. JSAC is used only when it is the name adopted by a cited study or framework. For an urban UAV, sensing and data transmission must share limited spectrum, hardware, and onboard energy while still providing situational awareness and sufficient throughput.

AI-based control can respond to changes in sensor observations, channel conditions, and UAV motion. CNNs and long short-term memory (LSTM) networks can learn spatial and temporal patterns from the available data. RL and multi-agent reinforcement learning (MARL) can then support action selection when the observations are incomplete. This does not imply that AI control is inherently fast. Decision latency also includes model inference, hardware execution, and data processing. Any claim of millisecond-level control should therefore be supported by measurements from the reported implementation.

The emphasis of AI-assisted JSAC varies across studies. Some methods adjust the flight path or transmission power to improve sensing accuracy. Others give priority to throughput, coverage, or link reliability, while joint methods optimize sensing and communication together [112, 113]. The distinction is important for a UAV because SWaP-C limits restrict the equipment that can be carried. In a tightly integrated design, sensing and communication share the transceiver, waveform, and spectrum, and sensing results can be passed directly to the communication controller. A loosely coupled design separates more of the processing and may be easier to build, although the additional processing stages can increase delay. A UAV prototype used a Software-Defined Radio payload to generate Synthetic Aperture Radar imagery while using communication waveforms [114]. The reported prototype demonstrates feasibility but does not by itself establish that the same architecture is optimal for every UAV mission.

The AI model depends on the sensing modality and control objective. CNNs can process images and spatial measurements, while LSTMs and recurrent neural networks model sequences such as vehicle trajectories or multipath fading. Radar, LiDAR, imagery, and communication data such as CSI may be fused at the sensor, feature, or decision level. The selected fusion level affects data volume, synchronization, and processing latency. Deep Deterministic Policy Gradient, Twin Delayed Deep Deterministic Policy Gradient, and multi-agent extensions such as Multi-Agent Deep Deterministic Policy Gradient can jointly adjust UAV trajectories, power, and beamforming. A UAV-enabled Internet of Things (IoT) study used joint 3D trajectory optimization with ISAC to improve radar estimation and energy efficiency under its evaluated configuration [115].

The reported performance gains are configuration-dependent. Multimodal fusion improved sensing accuracy by 24.2% in one study [116], while other work reported 33–50% higher sum rates than DRL baselines [113]. Li et al. [117] and

Zhou et al. [118] considered covert-transmission rate and energy efficiency, respectively, and a reduction of up to 50% in communication delay was reported in one evaluated method [116]. These values use different tasks, datasets, baselines, and objectives, so they should not be combined into a single JSAC benchmark. Inference times in the tens of milliseconds may support real-time control, but the processor, sensing-to-action pipeline, and communication overhead must also be specified.

AI-based JSAC can couple perception with communication and control, but its usefulness depends on observation quality, hardware sharing, and the training objective. Future evaluations should report these conditions together with sensing accuracy, data rate, energy consumption, and latency.

4.5. Optimization algorithms for real-time resource allocation

Resource allocation in an urban UAV network must respond to changing channels, traffic demands, mobility, and energy budgets. This subsection considers how classical, metaheuristic, and learning-assisted optimization methods are used when decisions must be updated during network operation. SCA and the Dinkelbach method are suitable for convex or near-convex formulations such as spectrum scheduling and power control [119]. PSO and GA can search non-convex spaces when a closed-form solution is unavailable, although they do not guarantee a globally optimal result [120]. Recent studies combine these procedures with ML or federated learning so that channel prediction, demand estimation, or distributed updates can inform the next allocation decision. The relevant comparison is therefore not only convergence speed but also the information required, update frequency, and communication overhead.

Hybrid ML-optimization frameworks connect data-driven prediction with a constrained optimization step. In one direction, solutions obtained from classical or metaheuristic methods can initialize DRL training and reduce the time spent exploring poor policies. In the other direction, a neural model can predict traffic demand, channel maps, or mobility patterns and provide these estimates to a resource-allocation solver. The benefit depends on prediction error and on whether the optimization problem is solved often enough to use the updated information. An AC-DSOS method has been developed for constrained scheduling in UAV-aided networks [111]. Its reported energy and latency results should be interpreted together with the scheduling constraints and baseline used in that study.

Federated learning (FL) is relevant when resource-allocation decisions must be learned across UAVs or edge devices without collecting all raw data centrally. Local devices can send model parameters, such as channel or interference representations, to an aggregator using a procedure such as Federated Averaging. This arrangement can reduce direct data sharing, but it introduces communication rounds, client heterogeneity, and aggregation costs. A three-layer FL implementation reported reductions of 15–50% in system delay and total energy consumption and an improvement of 0.3–2% in final global-model accuracy [121]. Privacy-preserving FL combined with DRL has also been evaluated for model accuracy and federated execution time [122]. Decentralized federated scheduling reduced the number of convergence rounds by up to 35% relative to a centralized scheme in one study [123]. These values depend on client number, data distribution, model size, and communication protocol.

Large-scale urban UAV networks make these trade-offs more visible. Centralized optimization may require frequent state updates

and impose a high computation or signaling burden, whereas FL and hybrid DRL distribute part of the adaptation across UAVs and edge nodes. Distributed operation does not remove the cost: local training, model exchange, synchronization, and protection against stale or unreliable updates must be managed. Fluctuating channels and unpredictable mobility also create a mismatch between the data used to train a policy and the conditions in which it is applied. Practical evaluation should therefore report the update interval, communication overhead, convergence criterion, and energy cost together with allocation quality and latency.

4.6. Critical evaluation and future research directions

The methods reviewed in this section address different parts of the UAV decision process. Classical optimization is useful when the objective and constraints support an analytical formulation. ML and RL address different parts of the control problem. ML learns relationships in channel or mobility data and can be used to predict a future state. RL chooses a sequence of actions whose consequences may appear several steps later. JSAC supplies the controller with observations of the physical environment. The boundaries are not always sharp, but one method cannot simply replace another. A hybrid system might retain an analytical solver for explicit constraints, use ML to predict the channel, and assign online decisions to RL. This added structure is worthwhile only if the improvement exceeds the computation, data exchange, and interface costs that it introduces.

The limitations also differ. Classical optimization gives interpretable decisions and often has known convergence behavior, but the result is only as reliable as the assumed channel and mobility models. After training, ML can shorten prediction or pilot-search procedures; it may still fail when the deployment data differ from the training set. RL adjusts actions over time, although training is costly and good empirical results do not establish convergence in a large, nonstationary multi-agent system. JSAC provides additional context, but inaccurate measurements, data-fusion delay, and competition for shared hardware may reduce the expected gain. Rate or prediction accuracy is therefore only part of the comparison. The available data, update time, reliability, and energy demand also affect whether a method is practical.

These problems grow with the system size. More UAVs create more interacting decisions and communication links, while additional sensing modalities increase the amount of data that must be transferred, aligned, and processed. Centralized methods must maintain larger state and action spaces and exchange more information. Distributed or hierarchical architectures can move computation to UAVs and edge servers but introduce coordination and synchronization problems. SWaP-C limits also matter: a policy that performs well on a server may be impractical when its memory, processor time, and communication overhead are transferred to a UAV. Evaluations should report the number of agents, model size, update interval, and onboard resource use.

Hybrid architectures cannot be compared reliably when each is tested in a different scenario. Common evaluation settings are needed for distributed multi-agent control, federated and edge learning, physics-guided methods, foundation-model-assisted optimization, and hardware-aware co-design. The system description should separate learned functions from constraints enforced by an analytical solver. It should also state how uncertainty is represented and test what happens when deployment conditions differ from those used during development. Safety-sensitive missions require additional evidence on fault response and the interpretability of decisions. The main question is whether the

architecture improves the sensing–communication–control process as a whole, rather than producing a better value for one metric.

5. Research Challenges and Future Directions

UAV channel modeling, adaptive antennas, and intelligent optimization have each advanced considerably. The remaining difficulty is to make these components work reliably together in an urban deployment. Results obtained from analysis, simulation, or controlled experiments may change when the number of UAVs grows, the propagation environment varies, or operational and regulatory constraints are introduced. Communication, sensing, AI, and control must therefore be studied under the conditions in which the complete system will operate. This section discusses the technical and practical questions that remain open.

5.1. Challenges in urban UAV channel characterization

An urban UAV channel can change substantially over a short flight segment. Moving obstacles interrupt the link, high-rise buildings create strong reflections, and foliage adds absorption. Together, these effects shorten channel correlation and produce fading that is difficult to predict. Model development is further limited by the small number of large UAV measurement datasets, especially at millimeter-wave and THz frequencies. At these frequencies, errors in the assumed material properties or propagation behavior can lead to unreliable channel estimates.

Measurements collected in different cities and flight conditions need to follow a common procedure if they are to be compared or combined. The records should include high-frequency channel measurements together with time-aligned information about blockage events. One option is to calibrate ray-tracing models against field data. Generative adversarial networks and domain randomization may then be used to expand the range of simulated conditions and reduce the difference between simulation and deployment. Such datasets and hybrid models could improve channel prediction across urban densities and flight profiles rather than only at the original measurement site [29].

5.2. Challenges in 6G antenna system design for UAVs

As discussed in Section 3, RIS and metamaterial antennas can strengthen UAV links, but the gains predicted by ideal models are difficult to reproduce in hardware. An RIS may contain thousands of passive elements whose states must be synchronized and updated in real time. IQ imbalance, other circuit impairments, and incomplete reflection further reduce the achievable gain [48]. Onboard metamaterial antennas present a different set of problems. Their fabrication can be complex, their usable bandwidth may be limited, and the finished antenna must meet the UAV's SWaP-C limits. These are deployment constraints rather than minor implementation details.

For RIS, distributed synchronization and designs that remain functional under control or hardware errors could reduce the difference between ideal and measured performance. This work needs hardware and software to be designed together so that compensation is included in the control system. Onboard antennas require materials and structures that provide broadband operation with lower size and energy demand and that can be integrated into the airframe. Electromagnetic performance should be evaluated together with SWaP-C because additional gain has little

practical value if it reduces payload capacity or flight endurance. A deployment may also combine a fixed RIS with a rapidly steerable onboard antenna. With hardware impairments included in the optimization, such a system could provide a more robust urban UAV link than either component used alone.

5.3. Challenges in AI-driven UAV trajectory and communication optimization

Trajectory control, communication, and sensing are often optimized separately because they use different objectives and operate at different rates. This division keeps each problem manageable, but it can lead to decisions that are locally effective and poor for the UAV system as a whole. A fully joint solution creates the opposite problem: the computation may be too slow for online control. The AI models discussed in Section 4 also have limits in interpretation, training cost, and transfer to new conditions. A policy that works in one city may respond incorrectly to an unfamiliar street layout or blockage pattern. Such errors require particular attention when the UAV is carrying out a safety-critical task.

Not every part of the controller needs to be learned from data. Known channel and flight constraints can restrict the actions available to a physics-guided model. An interpretable RL policy can then expose the state information and reward terms that influenced a decision, making its behavior easier to inspect. Lightweight MARL reduces the computation needed for coordination. Semantic AI addresses a different cost by selecting which observations are relevant enough to process or transmit. The channel model, antenna controller, and communication policy must still exchange information; otherwise, an improvement in one layer may create a problem in another.

A UAV swarm also needs a practical way to update its models. Federated learning (FL) with secure aggregation allows the vehicles to combine local updates without sending all raw data to a central node. Each learning round nevertheless consumes radio resources, energy, and time. The number and frequency of updates must therefore fit within the swarm's communication and computing budget. Cross-layer control and distributed learning will be useful for Smart City Skyways only if they improve adaptation and coordination without reducing flight endurance or delaying safety-related decisions.

5.4. Standardization, validation, and regulatory perspectives

An urban UAV communication system has to satisfy technical standards and aviation rules as well as link-level performance targets. The 3rd Generation Partnership Project TR 36.777 [124] addresses aerial vehicles in cellular networks, and Release 17 includes provisions related to UAV identification. The International Telecommunication Union P.2040 [29] is relevant to material and propagation modeling at millimeter-wave and THz frequencies. This work forms part of the wider standardization path toward 6G. Aviation requirements are set through a separate process. In the United States and Europe, the Federal Aviation Administration and European Union Aviation Safety Agency regulate matters such as identification, airspace access, beyond-visual-LoS operation, airworthiness, and flight safety.

Much of the current evidence still comes from simulation or laboratory prototypes. Open testbeds and large field campaigns are less common, especially for RIS-assisted links, sub-THz channels, and UAV networks controlled by AI. This makes results from

different studies difficult to reproduce or compare. Common test cases and evaluation procedures would help. A Digital Twin can place propagation, vehicle dynamics, and communication behavior in the same experiment, but it is not a substitute for field data. Its predictions need to be checked against measurements from the environment it is intended to represent.

Regulation also affects the technical design. A spectrum-sharing model, for example, must reflect how UAVs and terrestrial users are permitted to use the band. Corridor allocation and joint communication–navigation design must account for airspace and safety rules. Shared datasets and test procedures would serve a similar purpose in evaluation by allowing technologies to be compared under the same conditions rather than under laboratory-specific assumptions.

Table 7 summarizes reported results for channel prediction, RIS-assisted links, and AI-based optimization. These values are useful as reference points, but each remains tied to the assumptions, hardware, and test environment of the original study. A deployable system is likely to mix measured channel models with learning-based prediction, combine RIS hardware with adaptive algorithms, and account for aviation rules during communication design. The relevant test is how these parts work together under a common benchmark. Evidence at this level is needed before UAV networks can be treated as reliable elements of Smart City Skyways and the wider urban communication and sensing infrastructure.

5.5. Overall outlook

Channel estimation, antenna control, and AI-based decision-making are often studied separately. A deployed UAV does not operate in this way. A new channel estimate may trigger a beam adjustment, which may in turn change the communication link or the selected flight path. Delays or errors at any point can affect the final decision. The permissible response is also limited by airspace and safety rules. The main design problem is therefore not simply

to improve each component but to make their updates consistent and timely during flight.

Evidence for this interaction has to come from urban trials. A result obtained with one antenna, simulator, or sensing platform may not hold after any of them is replaced. Tests at several sites should record traffic, blockage, interference, and flight restrictions using compatible procedures. System interfaces must also allow algorithms to exchange data with different communication and sensing hardware. These tests would provide a firmer basis for deciding whether Smart City Skyways can support routine sensing, connectivity, and autonomous UAV operation.

6. Conclusion

The review began with the urban propagation environment and the measurements needed to describe it. It then considered how RIS and metamaterial antennas respond to blockage and motion, before examining the algorithms used for prediction, resource allocation, and flight or link control. This sequence reflects how the system operates. The controller acts on channel information through hardware whose response is limited by its size, power demand, and update rate. Improvements reported for one part of this chain may have little effect if the other parts cannot use them.

Table 7 places the main quantitative results next to one another, but it is not an overall ranking. The studies used different frequencies, environments, baselines, hardware, and evaluation procedures. Their values are most useful when read with those conditions. Later work needs test protocols that can be repeated across laboratories and deployment sites. Digital Twin evaluation can assist with this comparison, provided that the simulated environment and UAV behavior are checked against field measurements. Standards and aviation rules must be included in the same process because they restrict the available spectrum, flight path, and operating procedure.

Table 7
Unified summary of key performance indicators

Technical area	Key performance metric	Quantitative result
Channel characterization	Vision-aided blockage prediction accuracy	86% accuracy for predicting line-of-sight disruptions
Antenna system design	Active RIS sum-rate gain	Up to 130% gain over passive RIS counterparts
ML	Pilot overhead reduction	Up to 82% reduction compared to traditional methods
ML	Spectral-efficiency improvement	Up to 250% improvement in specific scenarios
RL	Energy efficiency gain	55–80% gains over conventional schemes
RL	Data rate increase (RIS-assisted)	34% throughput boost; ≈47% gain over non-learning baselines
JSAC	Sensing accuracy	24.2% improvement via multimodal data fusion
JSAC	Communication throughput	33%–50% higher sum rates than DRL baselines
JSAC	Communication latency	Up to 50% reduction in communication delay
FL	System delay and energy consumption	15–50% reduction
FL	FL communication rounds	Up to 35% reduction for convergence

The evidence base now needs to expand beyond the current test sites. Larger urban measurement campaigns would support channel models that cover more flight profiles and would give antenna designs a realistic setting for validation. With that foundation, reconfigurable antennas can be evaluated at larger scale, and interpretable AI can be tested for joint trajectory and communication control. Distributed learning among UAVs becomes relevant when these functions are extended to a swarm. A mature Smart City Skyways system would eventually have to coordinate all of them with sensing, navigation, flight control, and regulatory supervision.

The main conclusion is practical rather than tied to one algorithm or device. Channel characterization, antenna design, and communication-aware AI must exchange information at the rate required by the UAV mission and within the resources available on the platform. This interaction should be demonstrated during urban flight, not inferred only from separate simulations. If it remains reliable under real blockage, motion, interference, and safety constraints, a 6G UAV network could support urban communication, sensing, navigation, and autonomous aerial services.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Pengzhan Jiang: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Changying Xiang:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

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APPENDIX

A. Terminology

Abbreviations	Full Form
3GPP	3rd Generation Partnership Project
5G	Fifth-generation
6G	Sixth-generation
A2C	Advantage Actor-Critic
AWGN	Additive white Gaussian noise
BS	Base station
BVLOS	Beyond Visual Line of Sight Operations
CA-RIS	Centralized active RIS
CNN	Convolutional neural network
CRLH	Composite Right/Left-Handed
CSI	Channel-state information
DDPG	Deep Deterministic Policy Gradient
DQN	Deep Q-Network
DRL	Deep reinforcement learning
EASA	European Union Aviation Safety Agency
FAA	Federal Aviation Administration
FedAvg	Federated Averaging
FL	Federated learning
GA	Genetic algorithms
GNN	Graph neural network
HDRL-TSRAM	Hierarchical deep reinforcement learning based task scheduling and resource allocation method
ISAC	Integrated sensing and communication
ITU	International Telecommunication Union
JSAC	Joint sensing and communication
LNAs	Low-noise Amplifiers
LoS	Line-of-sight
LSTM	Long short-term memory
MARL	Multi-agent reinforcement learning
MDP	Markov decision process
ML	Machine learning
mmWave	Millimeter-wave
NLoS	Non-line-of-sight
NRW	Nicolson-Ross-Weir
PPO	Proximal Policy Optimization
PSO	Particle swarm optimization
RIS	Reconfigurable intelligent surfaces
RL	Reinforcement learning
SCA	Successive convex approximation

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Abbreviations	Full Form
SRR	Split-ring resonator
SWaP-C	Size, weight, power, and cost
TD3	Twin Delayed Deep Deterministic Policy Gradient
TE	Transverse electric
THz	Terahertz
TL	Transfer learning
TM	transverse magnetic
UAV	Unmanned aerial vehicle
UWB	Ultra-wideband